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Accounting for Epistemic Uncertainty in Mission Supportability Assessment: A Necessary Step in Understanding Risk and Logistics Requirements

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Future crewed missions to Mars present a maintenance logistics challenge that is unprecedented in human spaceflight. Mission endurance – defined as the time between resupply opportunities – will be significantly longer than previous missions, and therefore logistics planning horizons are longer and the impact of uncertainty is magnified. Maintenance logistics forecasting typically assumes that component failure rates are deterministically known and uses them to represent aleatory uncertainty, or uncertainty that is inherent to the process being examined. However, failure rates cannot be directly measured; rather, they are estimated based on similarity to other components or statistical analysis of observed failures. As a result, epistemic uncertainty – that is, uncertainty in knowledge of the process – exists in failure rate estimates that must be accounted for. Analyses that neglect epistemic uncertainty tend to significantly underestimate risk. Epistemic uncertainty can be reduced via operational experience; for example, the International Space Station (ISS) failure rate estimates are refined using a Bayesian update process. However, design changes may re-introduce epistemic uncertainty. Thus, there is a tradeoff between changing a design to reduce failure rates and operating a fixed design to reduce uncertainty. This paper examines the impact of epistemic uncertainty on maintenance logistics requirements for future Mars missions, using data from the ISS Environmental Control and Life Support System (ECLS) as a baseline for a case study. Sensitivity analyses are performed to investigate the impact of variations in failure rate estimates and epistemic uncertainty on spares mass. The results of these analyses and their implications for future system design and mission planning are discussed.

Nomenclature

α	=	sensitivity analysis multiplier
λ	=	failure rate
λ_m	=	mean failure rate
μ	=	lognormal distribution location parameter

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σ	=	lognormal distribution scale parameter
τ	=	mission endurance
C	=	confidence
C_{req}	=	required system-level confidence
m_i	=	mass of item i
n_i	=	number of spares provided for item i
POS_i	=	Probability of Sufficiency for item i
POS_{req}	=	required system-level Probability of Sufficiency

CCAA	Common Cabin Air Assembly
CDF	Cumulative Distribution Function
CDRA	Carbon Dioxide Removal Assembly
DSH	Deep Space Habitat
ECLS	Environmental Control and Life Support
EF	Error Factor
EMAT	Exploration Maintainability Analysis Tool
ISM	In-Space Manufacturing
ISS	International Space Station
LEO	Low Earth Orbit
LoC	Loss of Crew
MADS	Maintenance and Analysis Data Set
MTBF	Mean Time Between Failures
OGA	Oxygen Generation Assembly
P(LoC)	Probability of Loss of Crew
PDF	Probability Density Function
POS	Probability of Sufficiency
QPA	Quantity Per Application
TCCS	Trace Contaminant Control System
UPA	Urine Processor Assembly
WPA	Water Processor Assembly

I. Introduction

Future missions beyond Low Earth Orbit (LEO) present an unprecedented challenge for human spaceflight from the perspective of supportability – that is, the set of system characteristics that strongly influence the logistics and support required to enable safe and effective operation of systems.[1,2] Support requirements include deterministic logistics requirements such as consumables and life-limited items, as well as stochastic requirements for spare parts and maintenance supplies in response to random failures. In addition, the amount of crew time required to execute maintenance activities must be considered. All current and previous human spaceflight missions have either been of short duration (e.g. Space Shuttle, Apollo), or have been long-duration missions with regular resupply from Earth on regular, relatively short intervals (e.g. the International Space Station (ISS)). In either case, the overall mission endurance, defined as the time between resupply opportunities (including launch and landing),[3] has been short, ranging from days to months. In contrast, a mission to Mars will require systems that can sustain the crew for an endurance of 1,100 days, or approximately 3 years.[4] In addition, all previous missions have had the option to abort and return to Earth in a matter of days in the event of an emergency. This option will not be available on a mission to Mars. The combination of very long mission endurance and lack of abort options create a significant challenge for human spaceflight supportability and logistics management. Previous supportability strategies, which were often optimized for Earth-dependent operation in LEO, will no longer be effective for missions beyond LEO; new strategies must be developed to support the spaceflight systems of the future.[2,5–9]

Supportability is fundamentally a trade between risk and resources, due to the influence of stochastic maintenance demands on the need for supportability resources such as spare parts. Specifically, there is a risk that the spare parts provided will not be sufficient to cover all maintenance demands that occur during the mission. Spares are provided to reduce this risk to acceptable levels. The risk of insufficient spares is driven by both aleatory and epistemic uncertainty. Aleatory uncertainty results from natural randomness in the process being studied, while epistemic uncertainty results from a lack of knowledge about the process.[10] While aleatory uncertainty is typically accounted for

in supportability analyses by modeling the amount of time that a component will function before failure as a random variable (typically following an exponential distribution[11]) with a known failure rate, epistemic uncertainty is also present in the value of those failure rates. A component's failure rate cannot be directly measured, but must instead be estimated based upon statistical analysis of failure histories and/or comparison to similar components. Testing and operational experience provides additional data upon which to base these estimates. For example, aircraft or automobile designs typically have a large amount of operational experience gathered from long-term operation of many instances of the same unit, and this extensive experience can be very valuable for uncertainty reduction. However, when experience is limited or the population of test articles is low – as is typically the case for crewed spacecraft – a significant amount of epistemic uncertainty may remain in failure rate estimates. This remaining uncertainty can, in turn, have a very significant impact on supportability assessments and logistics forecasting for deep space missions.[9,12]

Variation in component reliabilities has an asymmetric impact on system-level supportability; put another way, the consequences of increased failure rates are greater than the benefits of reduced failure rates for a given item. System-level risk is the product of the risk associated with its constituent elements, and is therefore limited by the highest-risk element. If a single component has lower-than-expected reliability, the system-level risk at a given sparing level may be significantly higher, even if other components are more reliable than expected. As a result, epistemic uncertainty in failure rates tends to have a negative overall impact on system characteristics. When epistemic uncertainty is neglected, supportability analyses can significantly underestimate the amount of risk associated with a given level of maintenance resources. As a result, maintenance logistics forecasts that do not take into account epistemic uncertainty may significantly underestimate the amount of logistics required to provide sufficient risk coverage to a high degree of confidence.[9]

This paper examines the impact of both aleatory and epistemic uncertainty on maintenance logistics forecasting for crewed spacecraft. Both types of uncertainty are defined and their impacts on supportability are described. Models for each type of uncertainty are discussed, and a case study is examined with sensitivity analyses to isolate the impacts of variations in reliability estimates and uncertainty in those estimates. These results and their implications for human spaceflight mission development are then discussed. The remainder of this paper is structured as follows: Section II presents background regarding the role of uncertainty in supportability analysis, defining two types of uncertainty (aleatory and epistemic) and discussing the impacts that each has on maintenance logistics forecasting. Section III presents the modeling methodology used in this paper to examine maintenance logistics requirements as a function of both aleatory and epistemic uncertainty for a given mission, and Section IV applies this methodology to examine Environmental Control and Life Support (ECLS) maintenance logistics requirements for a notional Mars mission, along with sensitivity analyses to characterize the impacts of variations in both types of uncertainty independently. Section V discusses the results of this case study in the context of human spaceflight technology development, system design, and mission planning, and Section VI presents conclusions.

II. Background: Uncertainty and Supportability

Uncertainty is a major driver of maintenance logistics demand, which is in turn a significant driver of overall logistics demand for long-endurance missions.[2,5,9] Maintenance supplies, typically in the form of spare parts, must be provided in sufficient amounts to mitigate risk. On missions without timely abort or resupply options, the provision of sufficient spare parts is particularly important for critical systems such as ECLS, since a failure in these systems that goes unrepaired due to lack of resources could lead to Loss of Crew (LoC) when contingency options are limited. The probability that sufficient spare parts are provided for a given mission is captured by the Probability of Sufficiency (POS).[12,13] The overall system POS is the product of the POS for each item within the system. When abort and resupply are not available in a timely manner, POS for critical systems provides a bound on the Probability of Loss of Crew (P(LoC)):[14]

$$P(LoC) \geq 1 - POS \tag{1}$$

P(LoC) is a key risk metric used for human spaceflight mission planning,[10] and therefore equation 1 links the supportability level-metric POS to mission-level risk objectives. POS can be considered the "success probability" for maintenance logistics planning; the corresponding failure probability, $1 - POS$, is referred to as the maintenance logistics contribution to P(LoC).

Two key types of uncertainty are present in maintenance logistics forecasting:[10]

- Aleatory uncertainty, which is the result of natural randomness inherent to the process being examined. Uncertainty in the result of a coin flip using a coin of a known bias, for example, is aleatory.

- Epistemic uncertainty, which results from a lack of knowledge about the process. Continuing the previous example, if the bias of a given coin is unknown, uncertainty in that value is epistemic.

Aleatory uncertainty is commonly accounted for in supportability analyses in the form of a failure rate (λ) for each particular item, sometimes captured as a Mean Time Between Failures (MTBF). Failure rate is the inverse of MTBF, but either number serves the same purpose: to parametrize a probability distribution characterizing the random variable representing the amount of time that an item will operate before failure. An exponential distribution is typically assumed for first-order analyses of random failures,[15] and as a result the POS for a specific item, given its failure rate, is characterized by the Cumulative Distribution Function (CDF) of a Poisson distribution.[13] For more sophisticated analyses, such as those enabled by the Exploration Maintainability Analysis Tool (EMAT),[5,9,16] POS for individual items and/or the system as a whole can be characterized via Monte Carlo simulation of a given mission.

However, the direct use of a Poisson distribution (or Monte Carlo analysis, or any other stochastic assessment tool) to examine POS, assuming a known failure rate, neglects the epistemic uncertainty present in failure rate estimates. The inclusion of epistemic uncertainty introduces the need for an additional characterization of the analysis. Confidence (C) is a measure of the fidelity of a given estimate under a given amount of epistemic uncertainty; in this context, confidence is defined as the probability that the actual POS is greater than or equal to the estimated one.[12]

$$C = P(POS_{actual} \geq POS_{estimated}) \tag{2}$$

Put another way, confidence is the probability that an analysis does not underestimate risk. Both POS and confidence are critical considerations for supportability analysis when epistemic uncertainty is present, and failure to include epistemic uncertainty in supportability analyses can result in significant underestimates of risk and/or logistics mass requirements.[9]

III. Methodology

Many different models, incorporating various levels of fidelity, can be used to examine maintenance logistics requirements. These range from simple heuristics that calculate maintenance logistics mass as a percentage of system dry mass per year of operation[17,18] to sophisticated tools such as EMAT that use Monte Carlo simulations of entire missions to consider interactions between items and time-dependent effects.[5,9,16] In addition, since many different combinations of spares could achieve risk objectives, there is a need to apply an optimization algorithm to find (or approximate) the manifest that does so for minimum mass. Increased model fidelity and manifest optimality require increased computational resources; therefore, there is a need to balance the desired fidelity of the analysis output with the amount of resources to be allocated for it.[19] This analysis uses a mid-fidelity Poisson failure model, using Monte Carlo simulations to capture epistemic uncertainty, and applies a marginal analysis algorithm to approximate the optimal manifest that achieves risk objectives for minimum mass. Marginal analysis (described in greater detail in Section III.B below) is an optimization technique commonly used for spares manifests whereby the marginal value of each potential addition to the manifest is calculated by dividing the benefits of that item (i.e. reduction in risk) by its cost (i.e. mass). The item with the highest marginal value is added to the manifest, and the process is repeated until a desired risk objective is met.[13] This approach does not include all considerations that may affect the supportability analysis, and the optimization approach does not necessarily find the true optimum, but it provides a good tradeoff between model fidelity and resource requirements for early-stage analyses such as this.

A. Model

The analysis conducted in this paper assumes that failures occur at a constant rate, and therefore a Poisson distribution is used to model the distribution of the number of failures that may occur for a given item. POS for a specific item, given a failure rate λ, is then given by equation 3, where n is the number of spares provided for that item and τ is the mission endurance.

$$POS = \sum_{k=0}^{n} e^{-\lambda\tau} \frac{(\lambda\tau)^k}{k!} \tag{3}$$

A Monte Carlo approach is used to capture epistemic uncertainty, sampling failure rates from the failure rate uncertainty distribution for λ, which is assumed to be lognormal with Probability Density Function (PDF) given by equation 4.[10]

$$PDF(\lambda) = \frac{1}{\sqrt{2\pi}\sigma\lambda} e^{-\frac{1}{2}\left(\frac{\ln(\lambda)-\mu}{\sigma}\right)} \tag{4}$$

Here μ and σ are the location and scale parameters of the distribution, respectively. Lognormal distributions are used as failure rate prior distributions in the ISS MTBF Bayesian updating process, and are the recommended distribution for capturing uncertainty in parameters estimated from aggregate data sources such as component failure histories.[10,20,21] Each sampled failure rate in the Monte Carlo analysis is used to calculate POS, given that failure rate. The resulting set of sampled POS values is then used to determine confidence by calculating the fraction of sampled POS values that are above the required POS threshold.

B. Optimization

The objective of spares inventory optimization is to determine the number of spares to be provided for each item in order to achieve risk objectives (i.e. provide a required POS at a required confidence level) while minimizing the total mass of the spares inventory. This optimization problem is defined mathematically as follows

$$\text{Minimize} \quad \sum_i m_i n_i \tag{5}$$

$$\text{s.t.} \quad P\left(\prod_i POS_i(n_i) \geq POS_{req}\right) \geq C_{req} \tag{6}$$

where m_i is the mass of item i, n_i is the number of spares provided for item i, $POS_i(n_i)$ is the POS for item i given a certain number of spares, POS_{req} is the required POS for the system, and C_{req} is the required confidence. In order to solve this optimization problem, marginal analysis is used.[13] This optimization approach is similar to that previously used by Lange and Anderson,[22] Stromgren et al.,[5] and Owens and de Weck;[14,23] however, in this case the value being increased in the marginal analysis algorithm is not POS itself, but rather confidence at an associated POS level.

For each analysis, a manifest is initialized to a known lower bound for each spare in order to begin the marginal analysis algorithm at a partially completed manifest rather than having to build it from scratch, thus saving computational time. For each item, this lower bound is equal to either the number of spares required for scheduled maintenance (based on life limits) or the number required so that the item achieves POS/confidence requirements individually, whichever is larger. Since the overall system POS is the product of the POS for each individual item, all of which are between 0 and 1, any manifest for which individual line items do not achieve POS/confidence requirements is known to not achieve those requirements as a whole. Once the manifest is initialized at this lower bound, the initial confidence level is calculated using the methodology outlined in Section A. Then, for each item, the marginal value of an additional spare is determined by calculating the confidence increase associated with providing another spare for that item and dividing by the mass of the item. That is, the marginal value of an item is the confidence increase per unit mass that another spare for that item could provide. The spare that provides the greatest marginal value is added to the inventory, and the process is repeated until the confidence level is above the required threshold – that is, until the constraint defined in equation 6 is met. In some cases, during the early phases of marginal analysis, all options will have 0 value because no single item is sufficient to enable any of the Monte Carlo simulations to achieve the desired POS value. In order to overcome this issue, the algorithm implemented here includes a startup phase in which the marginal value for each item is calculated using the increase in median POS resulting from the addition of a spare for that item rather than using confidence. This startup phase is continued until confidence reaches a predefined startup threshold value, which for this paper was set at 0.01. Once the manifest confidence level rises above this value, the standard confidence-based marginal analysis approach is used for the remainder of the manifest optimization.

The end result of marginal analysis is a sequence of points forming a mass-confidence curve. Each discrete point along this curve represents a specific manifest along the mass-confidence Pareto frontier. As discussed by Owens and de Weck,[23] these points are Pareto-optimal, but they do not necessarily represent the minimum-mass manifest that achieves a given risk requirement. Other, nondominated solutions that achieve the desired POS and confidence for lower mass may exist. An algorithm to find the truly optimal solution is described by Owens and de Weck,[23] but the increased computational cost of the Monte Carlo portion of this analysis precludes its use for this paper in its current form. However, the piecewise-linear curve defined by the Pareto-optimal points found via marginal analysis does place a lower bound on the amount of mass that is required to achieve a given risk objective. Interpolation between adjacent points is used to find the mass value at which the Pareto frontier crosses the confidence threshold, which provides a slightly optimistic approximation of maintenance logistics mass. While this value slightly underestimates the amount of mass that may actually be required, in practice it tends to provide a better approximation of total mass than the first Pareto-optimal point above the threshold found via marginal analysis.

C. Data Sources

The ISS Maintenance and Analysis Data Set (MADS) captures the current state of knowledge of failure rates – based on initial estimates and Bayesian updates on those estimates using failure histories – for repairable items on board the station in terms of a current Bayesian mean MTBF estimate and an Error Factor (EF). EF captures the level of uncertainty in the estimate, and is defined as the ratio between the 95th and 50th percentile (or, equivalently, the 50th and 5th percentile) values of the distribution. Therefore, μ and σ for the lognormal distribution defined in equation 4 can be calculated based on the mean failure rate λ_m and the EF using equations 7 and 8.[10]

$$\sigma = \frac{\ln(EF)}{1.645} \tag{7}$$

$$\mu = \ln(\lambda_m) - \frac{\sigma^2}{2} \tag{8}$$

IV. Case Study: Notional Mars Deep Space Habitat

As an illustrative example, this paper examines the maintenance logistics mass required to achieve various POS and confidence requirements for a notional Mars mission. Mission endurance is assumed to be 1,100 days,[4] and supportability analysis is conducted for Deep Space Habitat (DSH) ECLS systems. The specific systems examined include:

- Oxygen Generation Assembly (OGA)
- Carbon Dioxide Removal Assembly (CDRA)
- Common Cabin Air Assembly (CCAA)
- Trace Contaminant Control System (TCCS)
- Urine Processor Assembly (UPA)
- Water Processor Assembly (WPA)

System characteristics, including masses, failure rate distributions, Quantity Per Application (QPA), life limits, and k-factors are assumed to be ISS-like, and are based on MADS data wherever possible.* If a specific DSH item does not appear in MADS, or if no Bayesian update data are available to provide failure rate estimates or EFs, data for that

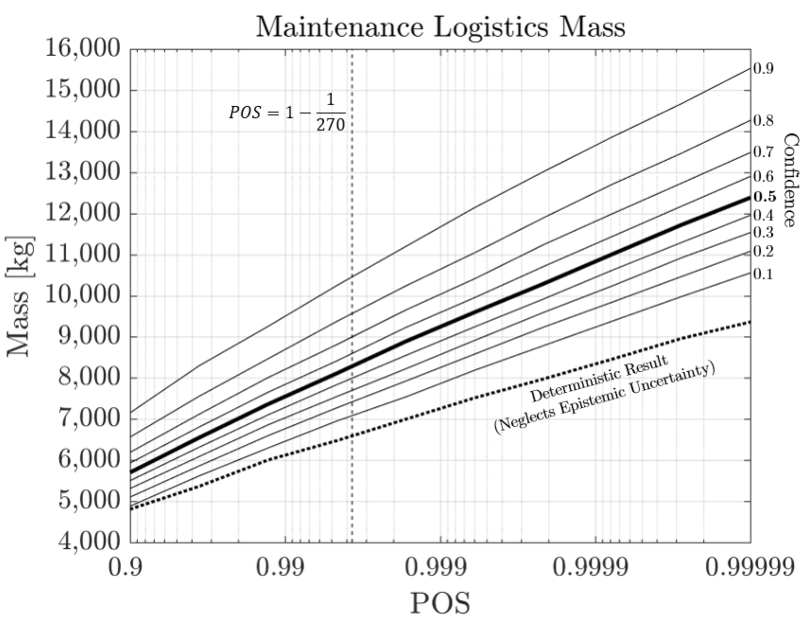

Figure 1. Maintenance logistics mass as a function of POS and confidence requirements. Results from deterministic manifest optimization, which neglects epistemic uncertainty, are also shown by the dotted black line. The baseline POS of $1 - \frac{1}{270}$ is indicated by the vertical dashed line. Note that POS is shown on a logarithmic scale.

* MADS data used for this paper are current as of February 12, 2017

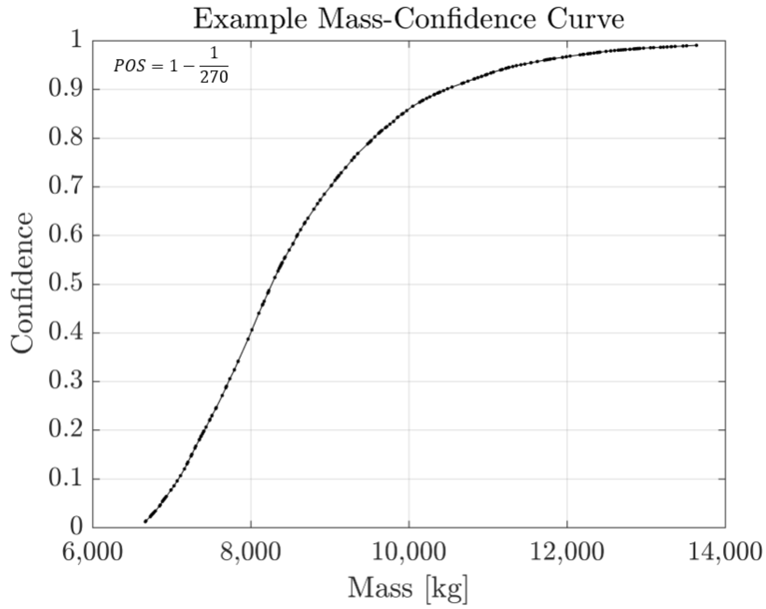

Figure 2. Example mass-confidence curve, for a baseline POS of $1 - \frac{1}{270}$. Confidence levels between 0.01 and 0.99 are captured. Each point represents a specific, Pareto-optimal manifest found via marginal analysis, and the line segments between them represent the lower bound on the mass required to achieve the corresponding level of confidence.

item are estimated based upon similarity to other items. Maintenance logistics mass requirements are calculated for POS values between 0.9 and 0.99999 and confidence levels ranging from 0.1 to 0.9 in increments of 0.1. For each assessment, 25,000 Monte Carlo simulations were executed. For comparison, maintenance logistics mass requirements were also calculated assuming that failure rates were deterministically known (i.e. neglecting epistemic uncertainty), with values based on the Bayesian mean MTBF estimate from MADS. Finally, a sensitivity analysis was conducted to examine the impact of variations in failure rates and EFs.

Figure 1 shows the maintenance logistics mass required for the notional DSH ECLS systems examined here. Mass requirements are shown for specific confidence levels across a range of POS values. In addition, the mass requirements calculated when epistemic uncertainty is neglected is shown by the black dotted line. Confidence levels are indicated by solid line, with their confidence values labeled in the upper right. For ease of reading, the line corresponding to a confidence of 0.5 is bolded. For comparison, a baseline POS of $1 - \frac{1}{270}$, or approximately 0.9963 – based upon the mean P(LoC) requirement of no greater than 1 in 270 for commercial crew transportation systems[24] – is used to examine confidence as a function of spares mass, shown in Figure 2 for confidence levels between 0.01 and 0.99. Each dot represents a specific, Pareto-optimal manifest, and the line segments between them represent a lower bound on the mass required to achieve the corresponding level of confidence, as described in Section III.B above. The vertical dashed line in Figure 1 corresponds to this baseline POS level.

In addition, two sensitivity analyses are conducted to examine the impact of variations in failure rates and uncertainty, assuming the baseline POS described above. Failure rates for all items are varied between 0.1 and 1.2 times their current values in order to examine the impact of increases and decreases in reliability. Since EF is the ratio between the 95^{th} and 50^{th} percentiles of the failure rate uncertainty distribution, it must be greater than or equal to 1 in order to be valid. Therefore, sensitivity to changes in EF cannot be examined through a direct multiplier, as was done for failure rates. Instead, the distance between the current EF and 1 was varied according to a multiplier, α, thus varying the amount of uncertainty in the failure rate estimate. A multiplier of 1 corresponds to the baseline case (no change), while a multiplier of 0 would correspond to a case with no uncertainty. The equations relating the sensitivity analysis value of failure rates and EFs as a function of this multiplier are:

$$\lambda' = \alpha\lambda \tag{9}$$

$$EF' = 1 + \alpha(1 - EF) \tag{10}$$

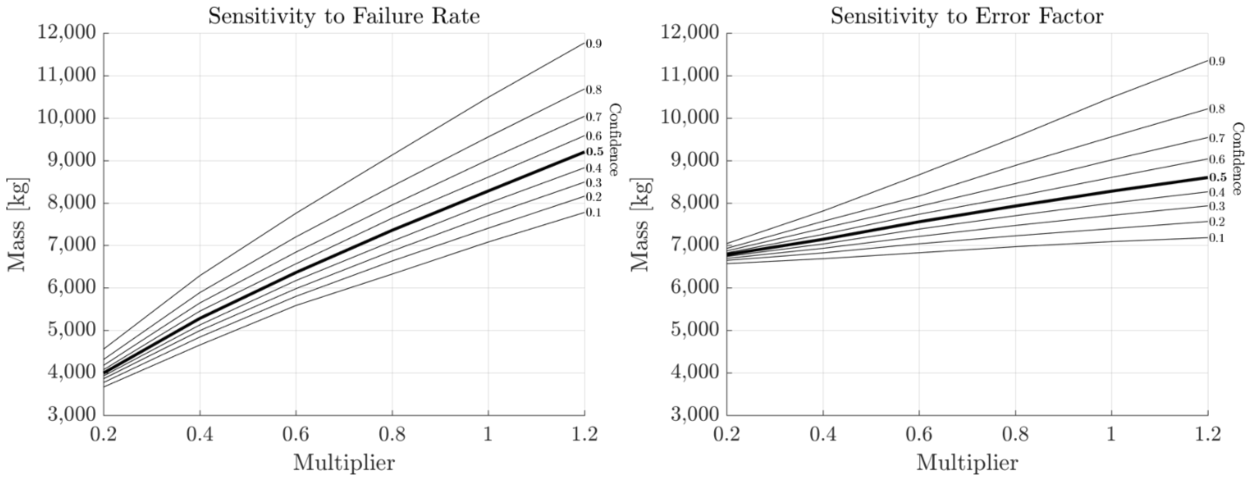

Figure 3. Sensitivity analysis results, showing maintenance logistics mass requirements when the failure rate (left) or error factor (right) for all items in the system are varied according to a multiplier α, as described by equations 9 and 10.

Here λ and EF are the original values for the failure rate and EF for a given item, respectively, and λ' and EF' are their values after application of the multiplier α. The results of both of these sensitivity analyses are shown in Figure 3.

V. Discussion

A. POS and Confidence Requirement Impacts on Mass

Figure 1 shows that both POS and confidence requirements are strong drivers of maintenance logistics mass demands. Increased POS results in exponential growth in mass requirements; similarly, mass grows exponentially with higher confidence requirements. As an example, at a POS of 0.99, an increase in confidence from 0.7 to 0.8 requires the addition of 547 kg of spare parts. A further increase in confidence from 0.8 to 0.9, in contrast, requires 921 kg, nearly 1.7 times as much mass. At higher POS levels, the extra mass required to increase confidence also increases. An increase in confidence from 0.7 to 0.8 at a POS of 0.99999 requires an additional 782 kg, and an increase from 0.8 to 0.9 requires an additional 1,264 kg. Both POS and confidence are required in order to ensure that the system is maintained over the course of the mission, and both correspond to higher logistics mass requirements. Mission designers must carefully balance the two.

Importantly, this analysis reaffirms the results of Stromgren et al.[9] in showing that analyses that neglect epistemic uncertainty seriously underestimate the amount of risk associated with a given level of logistics, or the mass required to drive risk down to acceptable levels. As Figure 1 shows, the dotted line indicating the mass requirement estimated using deterministic failure rates is significantly below the 0.1 confidence level. A supportability analysis that assumes that there is no uncertainty in failure rates may result in a mass allocation that is not even sufficient to provide a confidence of 1 in 10 that risk objectives are met. As POS requirements grow, this gap between the deterministic result and the result that includes epistemic uncertainty also grows.

B. Sensitivity to Failure Rate and Epistemic Uncertainty

Figure 3 shows that reduction in either failure rates or EFs can reduce the mass required to achieve a given confidence level. In both cases, the sensitivity is linearly related to the multiplier α, using the relationships defined in equations 9 and 10. Higher confidence levels are more sensitive to variation, and as a result the distance between confidence contours is reduced as either failure rate or EF are reduced.

An important effect is observed here regarding the relationship between the mean failure rate value and the impact of uncertainty in that value. This sensitivity analysis examined variations in failure rates and EF values independently. However, the left side of Figure 3 shows that as failure rate values are decreased, the distance between confidence contours also decreases, indicating a reduction in overall uncertainty. This is a result of the way that uncertainty is captured. Since EF defines the ratio between the 95th and 50th percentile values of the lognormal distribution representing failure rate uncertainty, and the parameters of that distribution – which influence the location of the median – are a function of the mean failure rate estimate (see equations 7 and 8), a reduction in mean failure rate means that the scale of uncertainty is lower at the same EF.

The benefits of reductions in uncertainty are limited by the amount of spares required in the deterministic case, as shown on the right side of Figure 3. Put another way, reducing uncertainty does not directly improve the system, but rather our understanding of it. The system will experience some unknown number of failures over the course of the mission, and will therefore need a corresponding set of spares in order to mitigate risk. Reducing uncertainty does not change the number of failures that will actually occur; it simply increases the analyst's ability to forecast that number and lowers the number of spares required to provide the desired confidence. In order to further reduce mass requirements below the amount required in the deterministic case, failure rates must also be increased.

However, improvement in failure rates requires redesign and remanufacture of systems, while uncertainty reduction requires only observation. Thus, uncertainty reduction may be less expensive than failure rate reduction. In addition, since failure rate reduction requires changes to the system, it may inadvertently introduce new failure modes and new uncertainties. Significant design changes may also invalidate previous experience on a system, effectively "resetting" uncertainty levels to higher values and incurring the corresponding logistics mass increase. Since uncertainty reduction can be purely observational, it does not have the risk of introducing new failure modes, and does not have the impact of invalidating previous experience. Reduction in both failure rates and uncertainties may be necessary to reduce logistics mass to acceptable levels, and both could be accomplished concurrently, since both require operational experience. However, they have different costs, risks, and benefits, and should be weighed appropriately by system designers during development and testing.

C. Implications for System Development

These analyses demonstrate the significant impact that epistemic uncertainty has on supportability for deep space missions. If the uncertainty in failure rate estimates is not taken into account during mission planning, mission risk and/or logistics requirements will be severely underestimated. However, an understanding of epistemic uncertainty and its impacts allows for more realistic planning, as well as identification of potential mitigation strategies. The most straightforward approach is to gain operational experience on systems in a relevant environment for statistically relevant periods of time. Depending on the level of acceptable risk, this may mean that systems must be tested for time periods much longer than their nominal mission. Therefore, system development activities must take into account the need to deliver completed systems, ready for testing, well before they will be applied in a mission-critical setting. Mission and campaign timelines must include time to operate and gain experience, or accept much higher risk and/or logistics mass requirements and operate with higher levels of uncertainty.

In addition, the value of design and operational heritage should not be underestimated. Evolutionary systems that build upon previous experience will likely have significantly lower uncertainty than completely new systems. However, the relevance of operational heritage should not be overestimated either. Designers must take care to understand the implications of changes between systems that have operated previously and the current design, and update uncertainty estimates accordingly. With careful planning and limited design changes, the use of a heritage system may result in logistics requirements lower than those for a new system, even if the new system has improved nominal performance, due to reduced uncertainty. System design and architecture decisions must balance the impact of increased uncertainty against the proposed performance improvements.

Finally, new technology may provide opportunities for new approaches to logistics. For example, In-Space Manufacturing (ISM) can enable an adaptable approach to spares logistics by manufacturing spare parts on-demand when they are needed from common raw materials. This on-demand manufacturing capability reduces logistics requirements directly by enabling the benefits of commonality between items of different designs, as long as they are constructed from the same material.[14,25] ISM also has the potential of mitigating the impact of uncertainty on logistics requirements, since it allows rebalancing of logistics resources among different types of spares during the mission. During the mission, items that exhibit higher-than-expected failure rates require more raw materials, but items that exhibit lower-than-expected failure rates require less. Without ISM, mission planners would have to pre-specify which spares are provided, and how many of each type; unused mass associated with a particular type of spare is wasted. When an ISM capability is available, a supply of raw materials is provided that can be specialized into different types of spare parts as needed, providing additional flexibility and reducing the total amount of spares logistics mass required to account for uncertainty.[14] However, new technology introduces significant new uncertainties. The impacts of the new uncertainty and risk introduced by a new technology must be carefully balanced against its potential benefit, and the amount of test time required to reduce those uncertainties to acceptable levels must be factored into technology development and mission planning timelines.

D. Assumptions, Limitations, and Future Work

This analysis assumed that failure rates were constant over time, that repairs are implemented immediately when a failure occurs, and that repairs require negligible time to implement. In addition, no distinction is made with regard

to when a failure occurs during a mission; the mission itself is not simulated on a day-by-day basis. These simplifying assumptions enable the use of Poisson distributions to model spares demand, significantly reducing modeling complexity, but they also reduce the fidelity of model results. However, for the purposes of this analysis, which is focused on understanding trends and sensitivities in maintenance logistics rather than on calculating exact cargo mass values, this level of fidelity is considered sufficient.

The current modeling approach relies on a Monte Carlo analysis to examine epistemic uncertainty, calculating POS for each manifest tens of thousands of times in order to determine confidence. While the assumption that POS for each item follows a Poisson distribution allows for rapid calculation of POS, this Monte Carlo approach is still time-consuming, especially given that manifest POS must be re-calculated repeatedly as spares are added in the marginal analysis algorithm. Future work will seek a closed-form solution (or approximation) to the distribution of POS given uncertainty distributions for failure rates in order to accelerate the manifest optimization process.

The sensitivity analysis in this paper varied parameters (mean failure rate or EF) for all items together by applying a multiplier, as described in equations 9 and 10. In application, it is likely that there are specific items for which focused effort to reduce failure rates and/or failure rate uncertainty would produce the greatest benefit. Future work will seek to identify these high-leverage items through more in-depth sensitivity analyses that examine the impacts of variations in failure rate and uncertainty for specific items or sets of items.

In addition, this analysis examined variations in failure rate and uncertainty independently. However, a key underlying factor in both of these parameters is time. Systems that allocate more time for testing and operational experience will have the opportunity to lower uncertainty regarding failure rates by observing failures and using the resulting data to update estimates. Similarly, observation of failures allows for the correction of those failures, though corrective action may increase uncertainty in some areas by introducing changes which negate the applicability of past experience to failure rate estimation. Future analyses will investigate the combined effect of variations in both failure rate and uncertainty jointly.

Finally, this analysis did not include any assessment of ISM impacts. Future work will combine ISM models that have been described in previous work with this epistemic analysis capability to build a holistic maintenance logistics analysis too.

VI. Conclusion

The systems that carry humans beyond LEO and out into the solar system will face supportability challenges unlike any that have been encountered in past spaceflight experience. They will need to operate independent from Earth, without access to timely resupply and without the option of timely abort home, for very long periods of time. A significant amount of maintenance resources will likely be required to reduce risk to acceptable levels. Uncertainty in parameter values (in this case, failure rates) adds another dimension to risk assessment beyond the pure probability of success or failure itself – namely, the confidence in that risk assessment. Analyses that neglect this uncertainty and assume that failure rate values are deterministically known will seriously underestimate the amount of risk associated with a given level of maintenance logistics, providing results that have very low confidence levels. This may impact mission planning by resulting in significant underestimates of the amount of maintenance logistics mass required to reduce risk to acceptable levels. Use of modeling techniques to incorporate epistemic uncertainty, such as those described in this paper, allows system designers to directly assess both POS and confidence and understand how both are impacted by variations in system parameters.

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References

[1] "NASA Systems Engineering Handbook (NASA/SP-2007-6105Rev1)," 2007.

[2] Cirillo, W., Aaseng, G., Goodliff, K., Stromgren, C., and Maxwell, A., "Supportability for Beyond Low Earth Orbit Missions," *AIAA SPACE 2011 Conference & Exposition*, Long Beach, CA: American Institute of Aeronautics and Astronautics, 2011, pp. 1–12.

[3] Do, S., "Towards Earth Independence -- Tradespace Exploration of Long-Duration Crewed Space System Architectures," Massachusetts Institute of Technology, 2016.

[4] Simon, M. A., Wald, S. I., Howe, A. S., and Toups, L., "Evolvable Mars Campaign Long Duration Habitation Strategies: Architectural Approaches to Enable Human Exploration Missions," *AIAA SPACE 2015 Conference and Exposition*, Pasadena, CA: American Institute of Aeronautics and Astronautics, 2015.

[5] Stromgren, C., Terry, M., Cirillo, W., Goodliff, K., and Maxwell, A., "Design and Application of the Exploration Maintainability Analysis Tool," *AIAA SPACE 2012 Conference & Exposition*, Pasadena, CA: American Institute of Aeronautics and Astronautics, 2012, pp. 1–14.
[6] Jones, H. W., Hodgson, E. W., and Kliss, M. H., "Life Support for Deep Space and Mars," *44th International Conference on Environmental Systems*, Tucson, AZ: 2014, pp. 1–15.
[7] Kennedy, K., Alexander, L., Landis, R., Linne, D., Mclemore, C., and Santiago-Maldonado, E., *Technology Area 07: Human Exploration Destination Systems Roadmap*, 2010.
[8] Hurlbert, K., Bagdigian, B., Carroll, C., Jeevarajan, A., Kliss, M., and Singh, B., *Technology Area 06: Human Health, Life Support, and Habitation Systems*, 2012.
[9] Stromgren, C., Goodliff, K., Cirillo, W., and Owens, A., "The Threat of Uncertainty -- Why Using Traditional Approaches for Evaluating Spacecraft Reliability Are Insufficient for Future Human Mars Missions," *AIAA SPACE 2016 Conference & Exposition*, Long Beach, CA: American Institute of Aeronautics and Astronautics, 2016.
[10] Stamatelatos, M., and Dezfuli, H., "Probabilistic Risk Assessment Procedures Guide for NASA Managers and Practitioners," 2011.
[11] Ebeling, C. E., *An Introduction to Reliability and Maintainability Engineering*, New Delhi: Tata McGraw-Hill Publishing Co. Ltd., 2000.
[12] Anderson, L., Carter-Journet, K., Box, N., DiFilippo, D., Harrington, S., Jackson, D., and Lutomski, M., "Challenges of Sustaining the International Space Station through 2020 and Beyond: Including Epistemic Uncertainty in Reassessing Confidence Targets," *AIAA SPACE 2012 Conference & Exposition*, Pasadena, CA: American Institute of Aeronautics and Astronautics, 2012.
[13] Sherbrooke, C. C., *Optimal Inventory Modeling of Systems: Multi-Echelon Techniques*, Boston, MA: Kluwer Academic Publishers, 2004.
[14] Owens, A. C., and de Weck, O. L., "Systems Analysis of In-Space Manufacturing Applications for the International Space Station and the Evolvable Mars Campaign," *AIAA SPACE 2016 Conference & Exposition*, Long Beach, CA: American Institute of Aeronautics and Astronautics, 2016.
[15] Ebeling, C. E., *An Introduction to Reliability and Maintainability Engineering*, New Delhi: Tata McGraw-Hill Publishing Co. Ltd., 2000.
[16] Stromgren, C., Terry, M., Mattfeld, B., Cirillo, W., Goodliff, K., Shyface, H., and Maxwell, A., "Assessment of Maintainability for Future Human Asteroid and Mars Missions," *AIAA Space 2013 Conference & Exposition*, San Diego, CA: American Institute of Aeronautics and Astronautics, 2013, pp. 1–15.
[17] Leath, K., and Green, J. L., "A Comparison of Space Station Utilization and Operations Planning to Historical Experience," *44th International Astronautical Congress*, Graz, Austria: IAF, 1993.
[18] Grenouilleau, J.-C., "Space Logistics Support," *Human Spaceflight Mission Analysis and Design*, W.J. Larson and L.K. Pranke, eds., New York: McGraw-Hill Higher Education, 1999.
[19] Owens, A., de Weck, O., Mattfeld, B., Stromgren, C., and Cirillo, W., "Comparison of Spares Logistics Analysis Techniques for Long Duration Human Spaceflight," *45th International Conference on Environmental Systems*, Bellevue, WA: International Conference on Environmental Systems, 2015.
[20] Vitali, R., and Lutomski, M. G., "Derivation of Failure Rates and Probability of Failures for the International Space Station Probabilistic Risk Assessment study," *Probabilistic Safety Assessment and Management*, London: Springer London, 2004, pp. 1194–1199.
[21] Dezfuli, H., Kelly, D., Smith, C., Vedros, K., and Galyean, W., "Bayesian Inference for NASA Probabilistic Risk and Reliability Analysis (NASA/SP-2009-569)," 2009.
[22] Lange, K., and Anderson, M., "Reliability Impacts in Life Support Architecture and Technology Selection," *42nd International Conference on Environmental Systems*, San Diego, CA: American Institute of Aeronautics and Astronautics, 2012, pp. 1–17.
[23] Owens, A. C., and de Weck, O. L., "Increasing the Fidelity of Maintenance Logistics Representation in Breakeven Plots," *46th International Conference on Environmental Systems*, Vienna, Austria: International Conference on Environmental Systems, 2016.
[24] Cooke, D. R., "Commercial Crew Transportation Systems Certification Requirements for NASA Low Earth Orbit Missions (ESMD-CCTSCR-10.10)," 2010.
[25] Owens, A., Do, S., Kurtz, A., and de Weck, O., "Benefits of Additive Manufacturing for Human Exploration of Mars," *45th International Conference on Environmental Systems*, Bellevue, WA: International Conference on Environmental Systems, 2015.